

## 基于对抗神经网络的恶意用户检测

第39组 蔡雨凡 闫璐





## **Task Definition**

## **Malicious detection**

Recently, a new type of attack, coined Sybil Account comes out targeting at social networks. Sybil are accounts that post fake reviews to a certain store or service in campaigns and get paid.

#### **Node classification**

Two type of information: the feature of the node and the network.

## **Graph Representation Learning**

Graph representation learning tries to embed each node of a graph into a low-dimensional vector space, which preserves the structural similarities or distances among the nodes in the original graph.



#### **Twitter:**

User-Network

This dataset consists of 81,306 nodes representing users and, 1,768,149 edges representing relationships.

http://snap.stanford.edu/data/ego-Twitter.html

User-Labels

This dataset is achieved from a paper called POISED: Spotting Twitter Spam Off the Beaten Paths. The tweets in this dataset were manually checked by a group of 14 security researchers who labeled them independently.

**dianping:** The dataset was crawled on Dianping from January 1, 2014 to June 15, 2015 and includes 10,541,931 reviews, 32,940 stores, and 3,555,154 users.

**Cora:** The dataset consist of 2708 scientific publications classified into one of seven classes. The citation network consists of 5429 links. Each publication in the dataset is described by a 0/1-valued work vector indicating the absence/presence of the corresponding word from the dictionary. The dictionary consists of 1433 unique words.



### **GNN**

#### **Convolution Neural Network – extract!**

- 1. Discrete convolution in CNN: filter for shared parameters
- 2. Convolution operation in CNN: [feature map] by calculating the central pixel point and the [weighted sum] of adjacent pixel points;

#### Reasons for studying GCN

- 1. CNN's [translation invariance] is not applicable on [non-matrix structure] data.
- 2. Hope to extract spatial features on the [topology map] for machine learning



## Two ways to extract the spatial features of [topology]

1. vertex domain (spatial domain):

operation: find the neighbors adjacent to each vertex, and use feature

representation

Examples: GraphSage

2. spectrum domain:

Spectral domain process:

- (1) Define the Fourier Transformation Fourier transform on the graph (using Spectral graph theory, study the properties of the graph by means of the eigenvalues and eigenvectors of the **Laplacian matrix of the graph**)
- (2) Define the convolution on the graph convolution Examples: GCN



## Laplacian matrix of the graph:

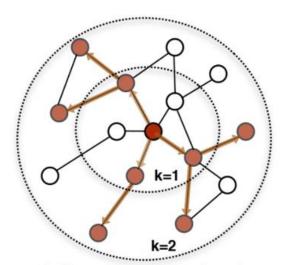
$$L = D - A$$

Where L is the Laplacian matrix and D is the degree matrix of the vertex (diagonal matrix), the elements on the diagonal are sequentially the degrees of the respective vertices, and A is the adjacency matrix of the graph.

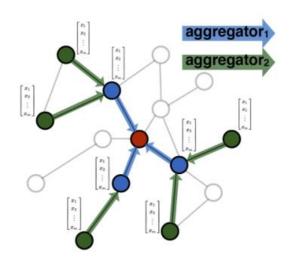
Labeled graph	D	Degree matrix				Adjacency matrix				Laplacian matrix									
<u></u>	/2	0	0	0	0	0 \	/0	1	0	0	1	0 \	1	2	$^{-1}$	0	0	-1	0
	0	3	0	0	0	0	1	0	1	0	1	0	11-	-1	3	-1	0	-1	0
(4)	0	0	2	0	0	0	0	1	0	1	0	0		0	-1	2	-1	0	0
Y LD	0	0	0	3	0	0	0	0	1	0	1	1		0	0	-1	3	-1	-1
3-2	0	0	0	0	3	0	1	1	0	1	0	0	-	-1	-1	0	-1	3	0
3	0	0	0	0	0	1)	0	0	0	1	0	0/		0	0	0	-1	0	1



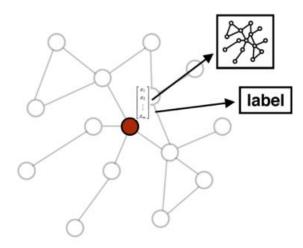
## GraphSage



1. Sample neighborhood



2. Aggregate feature information from neighbors



3. Predict graph context and label using aggregated information



## **GAN**

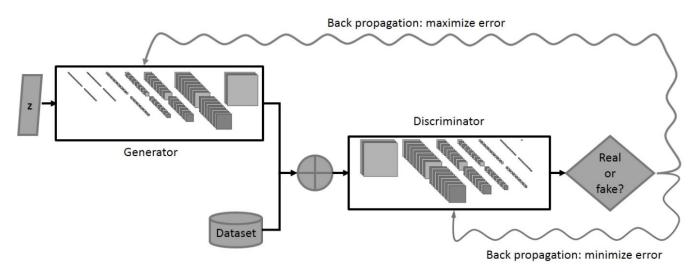


Fig 1.0, Source: Nvidia.

$$\min_{G} \max_{D} V(D,G) = \mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z} \sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log (1 - D(G(\boldsymbol{z})))].$$

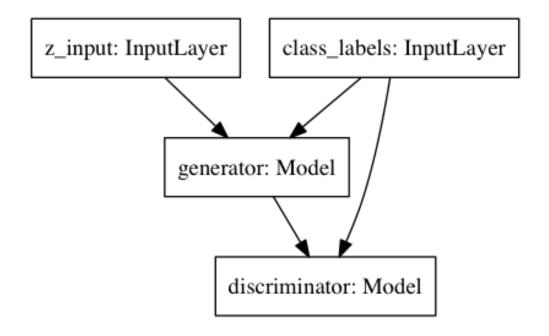
**Generator Loss:** 

**Discriminator Loss:** 

 $\frac{1}{m} \sum_{i=1}^{m} \left[ \log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right] \qquad \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)$ 



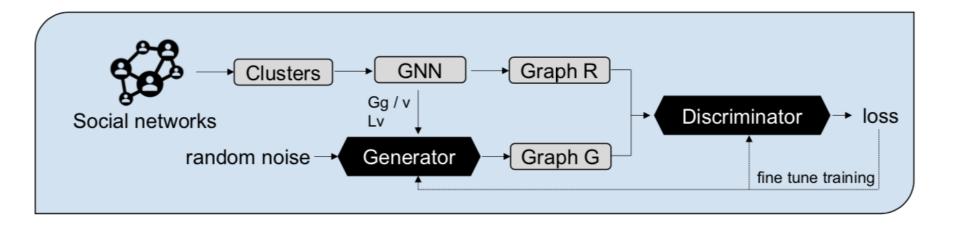
## **GAN**



Conditional-GAN: <a href="https://arxiv.org/abs/1411.1784">https://arxiv.org/abs/1411.1784</a>
Use random noise and real data with embedded labels as input



### GAN with GNN result



Random noise replaced by neighbor nodes' features predicted by GNN

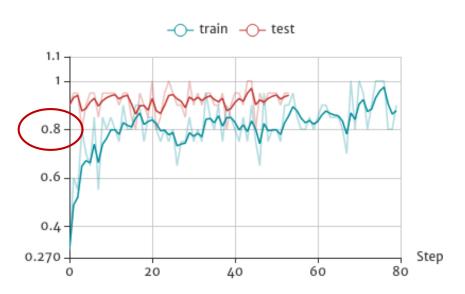


## **GAN**

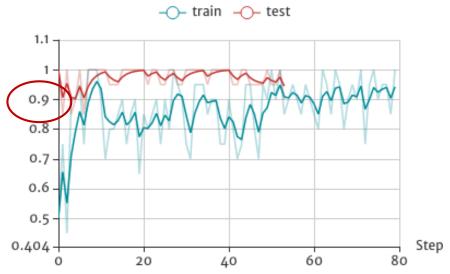
--training with random noise

--training with GNN result

discriminator/accuracy



discriminator/accuracy



Average test accuracy: 0.914815

Average test accuracy: 0.972222



## Results of Sybil dataset

	<b>Decision Tree</b>	SVM	GNB	KNN	Adabo ost	Rando m Forest	GCN/ Graph Sage (no featur e)	GAN (rando m)	GAN (+GC N)
Loss							0.344	0.109	0.173
Accu racy	0.659	0.677	0.875	0.595	0.785	0.897	0.80/ 0.81	0.913	0.963
Preci sion	0.828	0.716	0.832	0.817	0.817	0.847	0.811	0.951	0.962
recall	0.655	0.698	0.667	0.577	0.567	0.620	0.577	0.971	0.975



## Results of Cora dataset

	Decisi on Tree	SVM	GNB	KNN	Adabo ost	Rando m Forest	GCN	GAN (rando m)	GAN (+GC N)
loss							0.7207	0.458	0.283
Accura cy	0.618	0.647	0.484	0.427	0.557	0.664	0.8340	0.918	0.972
Precisi on	0.626	0.710	0.486	0.440	0.597	0.673	0.740	0.765	0.835
recall	0.626	0.646	0.484	0.427	0.557	0.657	0.811	0.972	0.976



## Analysis

# Thanks!

